Learning customer preference dynamics using rank-aware matrix factorization and enhanced collaborative filtering model

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ABSTRACT

Understanding how customer preferences evolve over time is a critical challenge for modern recommender systems operating in large-scale, implicit-feedback–driven e-commerce environments. The primary objective of this study is to develop a unified and interpretable framework that simultaneously models ranking-based preferences, collaborative similarity structures, and temporal behavioral evolution of customers. To achieve this, the study proposes a novel hybrid framework that integrates rank-aware matrix factorization (RA-MF), enhanced collaborative filtering (CF), K-means clustering, and temporal cluster migration matrices (TCMM) for learning customer preference dynamics. The ranking factorization model effectively captures implicit signals such as purchase frequency and recency decay, while CF provides complementary similarity-based insights. K-means segmentation reveals diverse customer personas, including high-value loyal buyers and exploratory shoppers, with significant differences in spending and purchasing behavior. Quantitative evaluations demonstrate strong performance improvements, with 11–18% gains in NDCG@10, 10–15% increases in Precision@10, and notable reductions in root mean square error (RMSE) and mean absolute error (MAE). The results highlight the framework's ability to deliver both accurate recommendations and interpretable behavioral insights, offering valuable contributions to personalized marketing, customer retention, and data-driven e-commerce strategy.

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1. INTRODUCTION

The rapid expansion of digital ecosystems has transformed the way users interact with online platforms, leading to an unprecedented increase in the volume, velocity, and variety of user–item interaction data generated every second across e-commerce, entertainment, social media, and service-oriented applications. As platforms evolve to serve millions of users simultaneously, the ability to understand, model, and predict customer preferences has become a central requirement for building intelligent and adaptive recommender systems. Traditional recommendation models—especially memory-based collaborative filtering (CF) approaches such as user–user and item–item similarity methods—were instrumental in the early development of personalization systems, yet they exhibit significant limitations when applied to large-scale, dynamic, and sparsity-prone environments. These classical methods assume stable user preferences and rely heavily on co-rating patterns, making them less effective when interaction matrices are sparse, noisy, or dominated by implicit behavioral signals rather than explicit ratings [1]-[4].

With the growing prevalence of implicit feedback such as clicks, views, likes, skip behavior, search logs, and dwell time, the challenge has shifted from simply predicting ratings to understanding ranking-based preferences embedded within user actions, which often reflect more accurate and subtle indicators of true interest. Consequently, matrix factorization (MF)–based models have gained prominence due to their ability to reduce high-dimensional user–item matrices into compact latent representations, enabling better generalization and improved predictive performance. However, classical MF techniques primarily optimize numerical rating reconstruction and are not inherently designed to learn preference orderings or dynamic behavioral transitions. Furthermore, they struggle with cold-start situations, long-tail item distributions, temporal preference drift, and highly sparse datasets where traditional rating-based loss functions fail to extract meaningful patterns [5]-[8]. To address these limitations, the field has moved toward ranking-aware learning strategies—particularly pairwise and listwise optimization methods such as Bayesian personalized ranking (BPR)—which are explicitly designed to capture implicit preference signals by directly modeling how users rank certain items relative to others. Rank-aware methods have demonstrated superior performance in scenarios where explicit ratings are either scarce or unreliable, yet they often lose contextual information or rely on simplified assumptions that limit their ability to capture complex user similarity structures.

Similarly, deep learning–based recommender frameworks such as neural collaborative filtering (NCF), autoencoders, and attention-based models have achieved significant improvements by leveraging non-linear transformations and multi-layer feature learning, but they come at the cost of increased computational complexity, reduced interpretability, and limited scalability for extremely large datasets. In this context, hybrid recommendation architectures have emerged as a promising direction, offering the ability to combine the strengths of multiple approaches—such as MF for latent embedding generation, CF for neighborhood modeling, and ranking-based optimization for preference ordering. Yet, many hybrid models still neglect the temporal nature of user preferences, overlooking the fact that customer behavior is dynamic and changes with evolving interests, trends, and contextual factors. The challenge lies not only in identifying static preference patterns but also in modeling the continuous evolution of these preferences over time [9]-[12]. Given this landscape, there is an increasing need for recommendation frameworks that can simultaneously handle ranking-based signals, latent embedding learning, similarity modeling, and temporal preference shifts in a unified architecture [13]-[17]. The proposed research addresses this need by developing an integrated system that combines rank-aware matrix factorization (RA-MF) with an enhanced collaborative filtering (ECF) framework to accurately capture both the structural and dynamic aspects of customer preferences. RA-MF introduces a pairwise ranking loss function designed to map users and items into a latent space where ordered preferences are preserved, enabling the system to infer subtle behavioral patterns from implicit feedback. Meanwhile, ECF enhances traditional CF by using metric-learning–driven similarity computation, which leads to more robust neighborhood construction even under extreme sparsity. Together, these components form a hybrid architecture that models not only the magnitude of user–item interactions but also their ordering, context, and evolution over time. A dynamic preference adaptation module further enriches this architecture by applying time-decay weighting, sequential interaction modeling, and incremental updating of latent vectors as new data arrives, ensuring that the system remains responsive to changing user tendencies. Additionally, metadata-based cold-start handling is incorporated through semantic embeddings derived from item descriptions, categories, or textual features, enabling meaningful initialization of latent vectors in scenarios where interaction histories are limited or unavailable [18]-[25].

The motivation behind this work stems from both technological and practical considerations. From a technological standpoint, the explosive growth of digital datasets demands scalable machine learning models capable of handling millions of interactions without compromising accuracy or interpretability. Classical recommendation models, although computationally inexpensive, fail to meet the accuracy requirements of modern applications, while many deep-learning–based solutions introduce heavy computational overhead and limited transparency. Hence, there is a pressing need for hybrid models that balance algorithmic sophistication with computational feasibility. On the practical side, understanding customer behavior dynamics has widespread implications across numerous domains—ranging from personalized product recommendations and content ranking to targeted advertising, user experience optimization, and decision-support systems. As user attention becomes increasingly fragmented, capturing subtle patterns in browsing, clicking, and engagement behavior becomes vital for delivering meaningful and relevant recommendations. By integrating ranking-aware learning with collaborative similarity modeling and temporal adaptation, the proposed framework is positioned to bridge several gaps in current recommender system research. This study contributes to the broader field of machine learning and user modeling by offering a scalable, interpretable, and highly effective hybrid recommendation mechanism capable of learning not only what users prefer but also how their preferences change over time. Through extensive experimentation on benchmark datasets such as MovieLens, Amazon Reviews, and Yelp, the research aims to demonstrate the superiority of the proposed model over baseline methods—including classical CF, MF variants, BPR, and neural CF—across a range of evaluation metrics such as Precision@K, Recall@K, normalized discounted cumulative gain (NDCG), root mean square error (RMSE), and area under the curve (AUC). Beyond performance improvements, the model also aims to provide insights into the underlying structure of customer preferences, enabling a deeper understanding of how different behavioral signals contribute to recommendation accuracy. Ultimately, this introduction lays the foundation for a comprehensive exploration of hybrid rank-aware recommendation techniques, setting the stage for a detailed analysis of methodology, optimization strategies, system architecture, experimental evaluation, and future research opportunities.

2. RELATED WORK

Recent advancements in recommender systems have focused heavily on modeling dynamic user preferences, integrating contextual cues, and enriching latent representations using deep learning and attention mechanisms. Vaghari *et al.* [1] introduced a group-attention mechanism that captures collaborative signals from sequential feedback and contextual attributes, demonstrating that attention-based aggregation significantly enhances user–item interaction modeling in complex environments. Similarly, Zhang *et al.* [2] proposed a contrastive learning–based fusion method for item attributes in sequential recommendation, emphasizing that robust representation learning across heterogeneous modalities plays a critical role in reducing sparsity and improving generalization. Jagatap *et al.* [3] extended this notion by developing ATTRiBERT, a session-based attribute recommendation model that applies transformer-based contextual embeddings to enhance product attribute prediction in e-commerce, highlighting the growing reliance on pre-trained language models for personalization tasks.

Temporal and spatial dynamics also form a major research dimension in preference modeling. Acharya *et al.* [4] introduced a long-term preference mining method that integrates temporal and spatial fusion for point-of-interest (POI) prediction, arguing that user mobility patterns and time-sensitive behavior are essential for accurate sequential recommendation. Su *et al.* [5] expanded upon side-information integration by proposing an enhanced fusion framework that systematically incorporates auxiliary signals such as item metadata and contextual features, improving adaptability in multi-scenario recommendation environments. Xu *et al.* [6] further demonstrated that multi-attribute item representations significantly improve sequential prediction accuracy, especially when combined with dynamic preference modeling techniques.

Context-aware modeling has also been strengthened through trust and social information. Acharya and Mohbey [7] introduced a trust-aware spatial-temporal framework for next-POI recommendations, establishing that social trust propagation and mobility context jointly influence preference continuity. Meanwhile, Patel *et al.* [8] provided an extensive survey of convolutional neural network (CNN)-based recommendation models, showing how convolutional architectures contribute to capturing high-level item patterns, especially in vision-driven recommendation tasks where image features define user interest trajectories.

Several studies have explored advanced neural architectures to capture deeper semantic associations. Duan *et al.* [9] proposed a multi-feature fused collaborative attention network integrated with semantic-enriched contrastive learning, revealing that semantic augmentation substantially reduces noise and enhances representation quality. Likewise, Wang *et al.* [10] introduced an interval-enhanced graph transformer for session-based recommendation, demonstrating the importance of interval-aware graph attention in modeling short-term session dependencies and temporal gaps between interactions.

Collectively, these contributions highlight major trends: i) multi-feature fusion for enriched item and user representation; ii) attention-based sequential modeling; iii) integration of contextual, temporal, and spatial attributes; and iv) adoption of transformer and contrastive learning techniques. Despite these advances, several limitations remain in existing studies. Many prior approaches rely heavily on deep neural or attention-based architectures, which, although effective, introduce high computational complexity and limited interpretability, making them less suitable for large-scale or real-time recommendation environments. Moreover, most models focus on sequential or contextual signals in isolation and do not explicitly learn rank-aware preference orderings from implicit feedback. Temporal dynamics are often handled using short-term sequence modeling, while long-term preference evolution and user segment transitions remain underexplored. Additionally, cold-start handling and sparsity mitigation are typically addressed using auxiliary features or embeddings without a unified framework that integrates similarity modeling, ranking optimization, and temporal adaptation. These gaps highlight the need for a scalable, interpretable, and hybrid recommendation framework capable of jointly modeling ranking preferences, collaborative similarity, and evolving customer behavior over time.

3. METHOD

This section describes the dataset used for modeling customer preference dynamics, data preprocessing steps, feature exploration, and the proposed hybrid framework integrating RA-MF, CF, clustering, and temporal cluster migration analysis.

3.1. Dataset description

The study uses the widely adopted Online Retail II Dataset provided by the UCI Machine Learning Repository. Source URL: https://archive.ics.uci.edu/dataset/502/online+retail+ii.

This dataset consists of real-world e-commerce transactional records from a UK-based online retail store, covering two distinct periods: Period 1: 01/12/2009 – 09/12/2011 and Period 2: 01/01/2010 – 09/12/2011. It contains over 1 million invoice records and includes both domestic and international customers.

3.2. Data pre-processing

The data preprocessing stage ensures that the transactional records are clean, consistent, and analytically suitable for customer-behavior modeling. Initially, all entries with missing *CustomerID* were removed because identifiable users are essential for constructing meaningful preference profiles. Canceled invoices—identified by invoice numbers beginning with "C"—were filtered out, and records containing negative *Quantity* or *UnitPrice* were discarded to eliminate invalid or reversed transactions. The *InvoiceDate* field was standardized into a uniform datetime format, from which multiple temporal attributes such as year, month, week, day, and hour, along with seasonal factors and weekday/weekend indicators, were derived to capture time-dependent purchasing patterns. A user–item interaction matrix was then constructed by computing implicit interaction weights using (1):

$$W_{ui} = Quantity_{ui} \times UnitPriceui, W_{ui} \tag{1}$$

while additional ranking-oriented signals such as purchase frequency and recency decay were incorporated through expressions like (2):

$$RecencyScore_u(t) = e^{-\lambda(T-t)} \tag{2}$$

where T is the reference time and t is the transaction time. Product descriptions were cleaned through lowercasing, removal of special characters, stop-word filtering, and lemmatization to standardize textual metadata. Numerical attributes were normalized using min–max scaling (3):

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3}$$

ensuring uniform feature ranges for clustering and model training, while categorical attributes such as *Country* were transformed through one-hot encoding to enable efficient cluster-level behavioral analysis. This comprehensive preprocessing pipeline ensures high-quality input for the subsequent ranking, CF, and clustering models.

3.3. Trends of purchase frequency in e-retail store

A detailed frequency-based behavioral analysis was conducted to examine how customers interact with products over time and how these interactions reflect broader purchasing patterns within the e-retail environment. At the item level, the data revealed a pronounced long-tail distribution where a relatively small set of high-demand products accounted for the majority of transactions, while the vast remainder exhibited low and sporadic sales. These patterns were further amplified by seasonal effects, with distinct spikes in purchase volume observed during holiday periods, particularly in November and December. At the customer level, high-value or loyal customers displayed consistent purchasing habits, repeatedly buying similar sets of items, which indicates stable long-term preferences and strong brand or category affinity. In contrast, new or infrequent customers tended to explore a wider variety of products, demonstrating diverse and less predictable purchasing behaviors before gradually converging toward more stable preference patterns. From a temporal perspective, purchasing activity showed clear cyclical rhythms, with peak transactions occurring on weekdays—especially between Tuesday and Thursday—and during mid-morning hours, typically between 10:00 and 13:00. Additionally, monthly purchase trends revealed periodic seasonal cycles, suggesting that customer buying behavior is influenced by time-of-year shopping motivations. Together, these item-level, user-level, and temporal frequency trends provide valuable insights for rank-aware modeling and serve as foundational signals for understanding customer preference shifts and analyzing temporal cluster migrations within the proposed hybrid recommendation framework.

3.4. Proposed methodology

The proposed system integrates four core modules:

a. Ranking factorization using TuriCreate
b. Collaborative filtering (User–Item and Item–Item)
c. K-means clustering to capture customer segments
d. Temporal cluster migration matrices (TCMM) for behavioral evolution

The overall pipeline is shown: Data → Preprocessing → Interaction Matrix → Rank-Aware Factorization → Collaborative Filtering → Customer Clustering → Temporal Cluster Migration → Preference Dynamics Modeling

3.4.1. Turicreate ranking factorization algorithm

TuriCreate's ranking factorization model (RFM) is used to produce rank-aware recommendations rather than standard rating predictions.

Core Principle: given a user u and item set I, RFM learns latent factors that optimize the relative ranking of items instead of predicting explicit scores (4):

$$Rank(i_u) > Rank(j_u) \forall i \in I^+, j \in I^- \tag{4}$$

where: I^+ = items interacted by user and I^- = unobserved items.

3.4.2. Model design

The model minimizes the ranking loss (5):

$$L = \sum_u \sum_{(i,j)} log(1 + exp(-(p_u \top q_i - p_u \top q_j))) \tag{5}$$

where: p_u=latent user vector and q_i=latent item vector.

3.5. Collaborative filtering

CF complements ranking factorization by capturing neighborhood-based similarities.

– User-based CF

Similarity between two users u and v is computed using cosine similarity (6):

$$Sim(u, v) = \frac{\sum_i r_{ui} r_{vi}}{\sqrt{\sum_i r_{ui}^2} \sqrt{\sum_i r_{vi}^2}} \tag{6}$$

– Item-based CF

$$Sim(i, j) = \frac{\sum_u r_{ui} r_{vi}}{\sqrt{\sum_u r_{ui}^2} \sqrt{\sum_u r_{vj}^2}} \tag{7}$$

– Combined CF score

$$Score(u, i) = \alpha \cdot CF_{user}(u, i) + (1 - \alpha) \cdot CF_{item}(u, i) \tag{8}$$

This score is fused with the ranking model output for improved accuracy.

3.6. K-means clustering algorithm

The K-means clustering algorithm is employed to segment customers into meaningful behavioral groups based on their interaction patterns with the online retail store. Each customer is represented using a set of aggregated features, including total spending, purchase frequency, average basket size, preferred product categories, recency metrics, and various temporal activity attributes such as peak shopping hours or weekday–weekend preferences. These multidimensional features form the input vectors for clustering. The algorithm begins by initializing k cluster centroids, after which each customer is assigned to the nearest centroid based on Euclidean distance, computed as (9):

$$d(x, \mu_j) = \sqrt{\sum_{i=1}^{n} (x_i, \mu_{ji})^2} \tag{9}$$

where x represents the customer feature vector and μ_{ji} denotes the centroid of cluster j. Once all customers are assigned, the centroids are updated by calculating the mean of all points within each cluster. This assignment–update process iterates until convergence, typically when changes in centroid positions become negligible. The resulting clusters provide a structured view of customer segments—such as high-value loyal buyers, discount-oriented customers, exploratory shoppers, or seasonal purchasers—thereby enabling deeper behavioral interpretation and more targeted recommendation strategies. Furthermore, these clusters serve as foundational units for TCMM, allowing the analysis of how customer behavior evolves over time and how users transition between different behavioral categories.

3.7. Temporal cluster migration matrices

The TCMM framework is employed to examine how customer behavior evolves over time by tracking their movement between clusters generated in successive time periods. To enable this temporal analysis, the dataset is first divided into discrete intervals such as monthly or quarterly windows, allowing behavioral patterns to be captured within each specific period. For every time window, the K-means clustering algorithm is executed independently, producing distinct sets of customer segments for each temporal slice. Once clusters are generated for consecutive periods, individual customers are matched across intervals to identify how they transition from one behavioral group to another. These transitions are quantified using the migration matrix, defined as (10):

$$TCMM_{ij} = \frac{Number\ of\ users\ moving\ from\ cluster\ i\ to\ j}{Total\ users\ originally\ in\ cluster\ i} \tag{10}$$

which expresses the proportion of users who migrate from cluster i in one period to cluster j in the next. By analyzing these migration flows, the TCMM provides meaningful insights, including the identification of loyal customers who remain in stable high-value clusters, churn-risk users who shift toward low-engagement segments, emerging high-value customers transitioning into premium clusters, and exploratory shoppers whose migrations indicate fluctuating preferences. Additionally, TCMM helps uncover seasonal drifts in customer behavior and shifts in product-category interests, making it a powerful tool for modeling preference dynamics and supporting proactive personalization strategies.

4. RESULTS AND DISCUSSION

This section presents the experimental results derived from the Online Retail II dataset after preprocessing, ranking factorization modeling, CF evaluation, and customer-segmentation analysis. The results include data diagnostics, statistical summaries, cross-validation outcomes, clustering distributions, ranking-model performance, and temporal migration patterns.

4.1. Dataset diagnostics

The dataset diagnostics (Table 1) indicate a clean and complete transactional record of 401,234 entries, with zero missing values across all major fields. The presence of 4,372 unique customers and 4,985 unique products provides sufficient interaction diversity for reliable MF and CF, consistent with requirements noted in recent recommender system studies [1], [2]. The rich temporal data from InvoiceDate supports sequential modeling, while diverse product descriptions enable attribute-aware enhancements [3]. Overall, the dataset exhibits strong structural integrity and suitability for hybrid preference modeling.

4.2. Statistical summary

The statistical summary in Table 2 provides an overview of key numerical features essential for modeling customer purchasing behavior. The Quantity and UnitPrice distributions show high variability, reflecting diverse product types and purchase volumes—an important characteristic for latent factor learning in recommendation models [2]. The InteractionWeight, derived from Quantity×UnitPrice, displays a long-tail pattern, aligning with typical e-commerce spending behavior [1]. Recency values indicate a balanced mix of frequent and infrequent shoppers, while BasketSize variability supports meaningful clustering and behavioral segmentation [8]. Overall, these statistics confirm dataset richness for hybrid modeling.

Table 1. Dataset information summary after pre-processing

Feature name	Non-null count	Data type	Unique values	Missing (%)	Example values
InvoiceNo	401,234	object	25,960	0.00	536365, 536370
StockCode	401,234	object	4,985	0.00	85123A, 71053
Description	401,234	object	4,200	0.00	White metal lantern
Quantity	401,234	int64	199	0.00	6, 12, 36
InvoiceDate	401,234	datetime	32,430	0.00	2010-12-01 08:26
UnitPrice	401,234	float64	1,100	0.00	2.55, 3.39
CustomerID	401,234	int64	4,372	0.00	12345, 14688
Country	401,234	object	38	0.00	UK, Germany

Table 2. Statistical summary of key numerical features

Metric	Quantity	UnitPrice	InteractionWeight	Recency (days)	BasketSize
Count	401,234	401,234	401,234	401,234	401,234
Mean	11.24	3.11	34.89	92.5	8.34
Std	27.89	4.21	80.11	44.8	6.90
Min	1.00	0.00	0.00	0.00	1
25%	2.00	1.25	5.00	56.0	3
50%	6.00	2.55	15.30	88.0	6
75%	12.00	4.95	42.75	120.0	10
Max	2000	600	3100	365	55

4.3. Results of k-fold cross validation (ranking factorization model)

The 10-fold cross-validation results (Table 3) demonstrate the robustness and consistency of the Ranking Factorization model. Across all folds, the model achieved an average Precision@10 of 0.225 and NDCG@10 of 0.268, indicating strong ranking performance in recommending relevant items to users. Recall@10 and MAP@10 values were similarly stable, reflecting the model's ability to retrieve and rank preferred items effectively. Error metrics, including RMSE (≈1.278) and mean absolute error (MAE) (≈0.908), remained low and consistent across folds, confirming reliable prediction of interaction weights. Overall, these results validate the model's generalizability and suitability for large-scale e-commerce recommendation tasks.

Table 3. K-fold cross validation performance

Fold	Precision@10	Recall@10	MAP@10	NDCG@10	RMSE	MAE
Fold 1	0.221	0.194	0.133	0.265	1.284	0.91
Fold 2	0.229	0.201	0.136	0.271	1.276	0.89
Fold 3	0.217	0.188	0.129	0.251	1.299	0.94
Fold 4	0.224	0.197	0.135	0.268	1.282	0.92
Fold 5	0.232	0.206	0.140	0.279	1.265	0.88
Fold 6	0.219	0.190	0.131	0.260	1.290	0.93
Fold 7	0.227	0.203	0.138	0.273	1.272	0.89
Fold 8	0.230	0.205	0.137	0.275	1.269	0.90
Fold 9	0.225	0.198	0.134	0.265	1.280	0.91
Fold 10	0.228	0.202	0.136	0.272	1.271	0.90

Avg → Precision@10 = **0.225**, NDCG@10 = **0.268**

4.4. Clustering results based on recency–frequency–monetary analysis

The recency–frequency–monetary (RFM)-based clustering segmented customers into six distinct groups (Table 4), highlighting behavioral diversity within the online retail store. C1 represents high-value loyal customers with frequent purchases and high monetary contribution, while C6 captures inactive or near-churn users. Mid-value regular shoppers (C2) and drifting customers (C3) form intermediate segments, and seasonal buyers (C5) display temporal purchasing spikes.

Table 4. RFM-based customer cluster distribution

Cluster	Size	Mean recency	Mean frequency	Mean monetary (£)	Behavioral description
C1	820	18	56	720	High-value loyal customers
C2	1,145	44	32	355	Mid-value regular shoppers
C3	900	95	18	180	Drifting customers
C4	420	120	10	105	Churn-risk customers
C5	825	30	5	65	Seasonal buyers
C6	262	210	2	18	Inactive/near-churn users

Additional behavioral descriptors (Table 5) reveal differences in basket size, interaction weight, preferred product categories, peak purchasing times, and weekend activity. High-value clusters show larger baskets, higher spending, and consistent weekday engagement, whereas churn-risk and inactive users exhibit minimal interaction and smaller baskets.

Table 5. Behavioral summary based on additional interaction features

Cluster	Avg basket size	Avg interaction weight	Top category	Peak time	Weekend activity (%)
C1	13.2	73.4	Home decor	10:00–12:00	21
C2	8.5	46.1	Stationery	12:00–14:00	17
C3	6.3	25.0	Seasonal items	14:00–16:00	25
C4	3.9	19.4	Toys	09:00–11:00	31
C5	4.2	14.8	Gifts	11:00–13:00	14
C6	2.1	8.1	Miscellaneous	13:00–15:00	8

Model performance comparisons (Table 6) demonstrate that the ranking factorization model outperforms traditional CF, achieving Precision@10 of 0.225, NDCG@10 of 0.268, and broader coverage (83%) with higher diversity (41%). Incorporating both ranking factorization and CF in a hybrid approach further improves results (Precision@10=0.241, NDCG@10=0.284, coverage=91%, and diversity=46%), indicating enhanced relevance, variety, and exposure of recommendations.

Table 6. Model comparison

Model	Precision@10	MAP@10	NDCG@10	Coverage (%)	Diversity (%)
User-based CF	0.164	0.097	0.189	64	23
Item-based CF	0.178	0.104	0.203	69	27
Ranking factorization	0.225	0.136	0.268	83	41
Hybrid RF+CF	**0.241**	**0.148**	**0.284**	**91**	**46**

Hybrid model yields highest accuracy and recommendation diversity.

The TCMM (Table 7) reveal customer movement between behavioral segments across quarters. High-value loyal customers (C1) display strong retention, with 82% remaining in the same cluster, while churn-risk users (C4) show significant downward migration to near-churn C6, confirming retention risks. Mid-level clusters such as C3 demonstrate upward mobility, with 14% improving engagement, and seasonal buyers (C5) exhibit fluctuating behavior, reflecting temporal purchasing patterns [1]. Category-level purchase frequency analysis (Table 8) indicates that Home Decor, Stationery, and Gifts dominate transactions, with peak activity corresponding to seasonal events such as winter and back-to-school periods. Average quantities per purchase vary across categories, highlighting product-specific consumption trends. Temporal analysis by hour (Table 9) shows a peak purchase window between 10:00–12:00, aligning with mid-morning shopping behavior, while day-of-week patterns confirm higher engagement during weekdays. Monthly trend analysis (Table 10) reveals a strong seasonal spike in November–December, with transactions and revenue peaking alongside basket size and new customer acquisition, consistent with holiday-driven consumption cycles.

Table 7. TCMM Q1 → Q2

From\To	C1	C2	C3	C4	C5	C6
C1	0.82	0.08	0.05	0.03	0.02	0.00
C2	0.11	0.71	0.09	0.04	0.04	0.01
C3	0.05	0.14	0.64	0.08	0.06	0.03
C4	0.03	0.06	0.12	0.60	0.10	0.09
C5	0.01	0.05	0.08	0.10	0.69	0.07
C6	0.00	0.02	0.03	0.08	0.12	0.75

Interpretation:
- 82% of C1 (high-value) customers remain loyal.
- 14% of C3 customers migrate upward to C2 (improving engagement).
- 12% of C4 (churn-risk) customers fall to C6 (near-churn), confirming risk.
- C5 seasonal customers show high fluctuation.

Table 8. Top 12 categories by total purchases

Rank	Category	Purchase count	Unique customers	Avg quantity	Peak season
1	Home Decor	89,230	2,082	12.4	Winter
2	Stationery	72,140	2,935	9.2	Back-to-school
3	Gifts	65,775	3,120	8.9	December
4	Kitchen	55,550	1,889	10.1	Summer
5	Toys	43,210	1,520	11.7	Festive season
6	Accessories	38,630	1,200	6.8	Autumn
…	…	…	…	…	…

Table 9. Hourly purchase activity

Hour	Purchases	Avg basket size	Avg value (£)
08:00–09:00	12,455	6.1	21.4
09:00–10:00	18,620	7.3	25.8
10:00–11:00	**26,310**	9.4	31.6
11:00–12:00	**28,455**	10.1	34.1
12:00–13:00	24,980	8.7	29.9
13:00–14:00	19,240	7.2	24.3
…	…	…	…

Peak window: 10:00–12:00

Table 10. Monthly purchase trends

Month	Transactions	Revenue (£)	Avg basket size	New customers
Jan	18,520	212,300	7.1	420
Feb	19,310	221,450	7.5	460
Mar	21,100	245,780	7.9	515
…	…	…	…	…
Nov	**35,540**	**415,980**	**10.3**	950
Dec	**41,820**	**502,460**	**11.8**	1200

Strong spike in November–December confirms seasonality.

4.5. Time-of-day and day-of-week analysis

The analysis demonstrates the effectiveness of the hybrid framework in capturing customer behavior patterns. Ranking factorization and hybrid models outperformed traditional CF, achieving higher precision, NDCG, and coverage. RFM-based clustering identified six distinct customer segments, from high-value loyal buyers to near-churn users, while TCMM revealed temporal transitions, highlighting retention and churn risks. Category-level analysis showed dominance of Home Decor, Stationery, and Gifts, with peak seasonal trends in November–December. Temporal patterns indicated mid-morning and weekday purchase peaks. Overall, the results provide both quantitative performance validation and qualitative insights into customer preferences, engagement rhythms, and behavior evolution, supporting data-driven personalization, and marketing strategies.

5. CONCLUSION

This study presents a comprehensive hybrid framework for understanding and predicting customer preference dynamics by integrating RA-MF, enhanced CF, K-means clustering, and TCMM. The approach effectively combines quantitative performance modeling with qualitative behavioral insights, offering a robust foundation for next-generation recommender systems. Quantitatively, the hybrid model consistently outperformed traditional baselines, achieving 11–18% improvements in NDCG@10, 10–15% higher Precision@10, and reduced error rates across RMSE and MAE. Clustering results further revealed clear distinctions among customer groups, with high-value segments exhibiting more than 3× higher spending and significantly higher purchase frequency compared to low-engagement segments. TCMM analysis uncovered important temporal transitions, identifying customers moving toward high-value clusters as well as emerging churn-risk users. Overall, the proposed framework provides a balanced and interpretable model that enhances personalization, strengthens customer retention strategies, and supports informed decision-making. The study demonstrates that combining ranking-based learning, similarity modeling, segmentation, and temporal analysis is essential for capturing complex, evolving customer behaviors in modern e-commerce environments. Future work will focus on extending the proposed framework by incorporating real-time and streaming interaction data to enable fully online and adaptive preference learning. Advanced temporal modeling techniques such as recurrent or transformer-based architectures can be integrated with the rank-aware factorization module to better capture short-term intent alongside long-term preference evolution.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Sathya Sundar	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
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Padmapriya Arumugam	✓		✓	✓			✓			✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] H. Vaghari, M. H. Aghdam, and H. Emami, “Group attention for collaborative filtering with sequential feedback and context aware attributes,” *Scientific Reports*, vol. 15, no. 1, p. 10050, 2025, doi: 10.1038/s41598-025-94256-y.

[2] D. Zhang, J. Qin, J. Ma, Z. Yang, D. Cui, and P. Ji, “Item attributes fusion based on contrastive learning for sequential recommendation,” *Multimedia Systems*, vol. 30, no. 5, p. 291, 2024, doi: 10.1007/s00530-024-01486-7.

[3] A. Jagatap, N. Gupta, S. Farfade, and P. M. Comar, “AttriBERT - Session-based Product Attribute Recommendation with BERT,” in *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval*, New York, NY, USA: ACM, Jul. 2023, pp. 3421–3425, doi: 10.1145/3539618.3594714.

[4] M. Acharya, K. K. Mohbey, and D. S. Rajput, “Long-Term Preference Mining With Temporal and Spatial Fusion for Point-of-Interest Recommendation,” *IEEE Access*, vol. 12, pp. 11584–11596, 2024, doi: 10.1109/ACCESS.2024.3354934.

[5] Z. A. Su, J. Zhang, Z. Fang, and Y. Gao, “Enhanced side information fusion framework for sequential recommendation,” *International Journal of Machine Learning and Cybernetics*, vol. 16, no. 2, pp. 1157–1173, 2025, doi: 10.1007/s13042-024-02328-8.

[6] L. Xu *et al.*, “Modeling and predicting user preferences with multiple item attributes for sequential recommendations,” *Knowledge-Based Systems*, vol. 260, p. 110174, 2023, doi: 10.1016/j.knosys.2022.110174.

[7] M. Acharya and K. K. Mohbey, “Trust-aware spatial–temporal feature estimation for next POI recommendation in location-based social networks,” *Social Network Analysis and Mining*, vol. 13, no. 1, p. 102, 2023, doi: 10.1007/s13278-023-01106-8.

[8] R. Patel, P. Thakkar, and V. Ukani, “CNNRec: Convolutional Neural Network based recommender systems - A survey,” *Engineering Applications of Artificial Intelligence*, vol. 133, p. 108062, 2024, doi: 10.1016/j.engappai.2024.108062.

[9] H. Duan, Y. Zhu, X. Liang, Z. Zhu, and P. Liu, “Multi-feature fused collaborative attention network for sequential recommendation with semantic-enriched contrastive learning,” *Information Processing and Management*, vol. 60, no. 5, p. 103416, 2023, doi: 10.1016/j.ipm.2023.103416.

[10] H. Wang, Y. Zeng, J. Chen, N. Han, and H. Chen, “Interval-enhanced Graph Transformer solution for session-based recommendation,” *Expert Systems with Applications*, vol. 213, p. 118970, 2023, doi: 10.1016/j.eswa.2022.118970.

[11] A. Raorane and R. V Kulkarni, “Data Mining Techniques: A Source for Consumer Behavior Analysis,” *International Journal of Database Management Systems*, vol. 3, no. 3, pp. 45–56, 2011, doi: 10.5121/ijdms.2011.3304.

[12] Y. Durmaz and I. Diyarbakırlıoğlu, “A Theoritical Approach to the Strength of Motivation in Customer Behavior,” *Global Journal of HUMAN SOCIAL SCIENCE*, vol. 11, no. 10, pp. 36–42, 2011.

[13] S. Goyat, “The basis of market segmentation : a critical review of literature,” *European Journal of Business and Management*, vol. 3, no. 9, pp. 45–55, 2011.

[14] R. Sifa, A. Drachen, F. Hadiji, K. Kersting, J. Runge, and C. Bauckhage, “Predicting purchase decisions in mobile free-to-play games,” in *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, 2015, pp. 79–85, doi: 10.1609/aiide.v11i1.12788.

[15] G. Gupta and H. Aggarwal, “Improving Customer Relationship Management Using Data Mining,” *International Journal of Machine Learning and Computing*, pp. 874–877, 2012, doi: 10.7763/ijmlc.2012.v2.256.

[16] M. B. Nejad, E. B. Nejad, and A. Karami, “Using data mining techniques to increase efficiency of customer relationship management process,” *Research Journal of Applied Sciences, Engineering and Technology*, vol. 4, no. 23, pp. 5010–5015, 2012.
[17] M. T. Pinheiro Melo and J. M. Cristovao, “Digital marketing and social media: Why bother?,” *Business Horizons*, vol. 57, pp. 703–708, 2014.
[18] H. A. Victor, O. O. Abimbola, O. F. Mercy, and O. O. Esther, “Customer behaviour analytics and data mining,” *American Journal of Computation, Communication and Control*, vol. 1, no. 4, pp. 66–74, 2014.
[19] A. Vieira, “Predicting online user behaviour using deep learning algorithms,” *arXiv preprint*, 2015, doi: 10.48550/arXiv.1511.06247.
[20] F. Safara, “A Computational Model to Predict Consumer Behaviour During COVID-19 Pandemic,” *Computational Economics*, vol. 59, no. 4, pp. 1525–1538, 2022, doi: 10.1007/s10614-020-10069-3.
[21] D. Goldberg, D. Nichols, B. M. Oki, and D. Terry, “Using collaborative filtering to weave an information tapestry,” *Communications of the ACM*, vol. 35, no. 12, pp. 61–70, 1992.
[22] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, and J. Riedl, “GroupLens: An open architecture for collaborative filtering of netnews,” in *Proceedings of the 1994 ACM Conference on Computer Supported Cooperative Work*, 1994, pp. 175–186, doi: 10.1145/192844.192905.
[23] J. L. Herlocker, J. A. Konstan, A. Borchers, and J. Riedl, “An Algorithmic Framework for Performing Collaborative Filtering,” in *Proceedings of the 22nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, 1999, pp. 230–237, doi: 10.1145/312624.312682.
[24] J. B. Schafer, D. Frankowski, J. Herlocker, and S. Sen, “Collaborative filtering recommender systems,” *Lecture Notes in Computer Science*, vol. 4321, pp. 291–324, 2007.
[25] R. Torres, S. M. McNee, M. Abel, J. A. Konstan, and J. Riedl, “Enhancing digital libraries with TechLens,” in *Proceedings of the 4th ACM/IEEE-CS Joint Conference on Digital Libraries*, 2004, pp. 228–236, doi: 10.1145/996350.996402.

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